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Comprehensive survey of body weight estimation: techniques, datasets, and applications

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Abstract
Accurate weight measurement is critical in emergency medicine, particularly for the precise administration of medications and treatments. However, traditional methods of weight estimation can be unreliable, especially in time-sensitive or resource-limited environments. This study provides a comprehensive review of the advancements and techniques in body weight estimation, with a focus on modern approaches leveraging contactless sensors, such as 3D cameras, and AI-powered computational models. The research evaluates the accuracy, reliability, and practical applicability of these methods across different contexts, including healthcare, forensic sciences, and emergency response. Additionally, this study identifies the limitations of current methodologies and uncovers gaps in the literature that warrant further investigation. Our findings aim to guide future research efforts and the development of more precise and scalable weight estimation solutions, ultimately enhancing their applicability in a variety of sectors.

Keywords Weight estimation · 3d camera · Depth · Emergency medicine · Drug delivery

Acronym

3D	3 Dimensional
2D	2 Dimensional
EMR	Electronic Medical Records
AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Network
DNN	Deep Neural Networks
UAE	United Arab Emirates
BMI	Body Mass Indexkl
MAE	Mean Abslute Error
RMSE	Root Mean Sqaure Error
CT	Computed Tomography
RGB	Red Blue Green

Extended author information available on the last page of the article

RGBD	Red Blue Green Depth
NHANES	National Health and Nutrition Examination Survey
DARWIN	Deformable Patient Avatar Representation With Deep Image Network
RANSAC	Random Sampling and Consensus
MRI	Magnetic Resonance Imaging
TVWE	Top-View Weight Estimation
CAESAR	Civilian American and European Surface Anthropometry Resource
CK	Cohn-Kanade
SLP	Simultaneously Lying Pose

1 Introduction and background

In the exigent domain of emergency medical care, precise and timely interventions are imperative for minimizing adverse outcomes and, ultimately, saving lives [1, 2]. Among the multitude of assessments and interventions performed by emergency medical professionals, accurate weight estimation is a fundamental, yet often overlooked, aspect [3]. While seemingly insignificant, the importance of precise weight estimation cannot be overstated, as it serves as a foundation for many clinical decisions, particularly in scenarios where obtaining actual weight measurements is impractical or impossible [4]. Accurate weight estimation is essential for guiding treatment decisions and optimizing medication dosing in emergency settings. Many life-saving interventions, including drug administration and fluid resuscitation, are weight-dependent, necessitating precise estimation techniques to avoid under- or overdosing [5]. Moreover, weight estimation assumes heightened significance in vulnerable patient populations, such as pediatric and geriatric patients, where variations in body composition and developmental stages necessitate tailored treatment approaches [6]. Failure to adjust treatment protocols based on accurate weight estimations can lead to suboptimal care and adverse outcomes in these vulnerable groups [7].

Existing methods of weight estimation in emergency medical care, while valuable, often fall short of providing the level of accuracy required for optimal patient care [3]. These methods of weight estimation face inherent limitations stemming from the limitations of the methods themselves, the complexity of patient anatomy and physiology, variability in clinical settings, and practical constraints [3]. While these methods serve as valuable tools for guiding clinical decision-making in the absence of actual weight measurements, ongoing efforts to improve their accuracy and reliability are essential for enhancing patient safety and treatment efficacy in emergency settings.

Patients' self-estimate of weight is the most accurate of all estimation methods. However, during emergency care, self-estimates may not be possible more than half the time, as patients may be confused or unresponsive, or may not know their weight. "Guesstimates" by family members and healthcare providers are often not accurate and may lead of significant dosing errors. Anthropometric-based methods such as the Lorenz method can be very accurate, but multiple measurements may be difficult to acquire during emergencies [8, 9]. The PAWPER XL-MAC tape, which was specifically designed for use during emergencies, has shown initial promise, but needs further validation. This leaves a substantial and important gap in this aspect of clinical care

The remainder of this paper is organized as follows: Section 2 provides a comprehensive literature review, detailing both traditional and AI-based methods for body weight estimation, alongside an exploration of relevant datasets and applications in various domains. Section 3 outlines future research directions and potential advancements in weight estimation techniques. Finally, Section 4 concludes the paper by summarizing key findings and highlighting the contributions of this study to the field.

1.1 Motivation

The use of 3D camera systems, driven by artificial intelligence analytical methods, is a potential solution to the problems experienced with existing emergency weight estimation. The potential benefits of weight estimation using 3D camera systems include:

- Precision and accuracy: 3D camera weight estimation leverages advanced imaging techniques and artificial intelligence to generate highly accurate and precise measurements of a patient's body dimensions. By capturing detailed anatomical data in three dimensions, including height, width, and depth, these systems can calculate weight with greater accuracy than visual estimation or length-based formulas.
- Non-invasive and rapid assessment: Unlike conventional weight measurement methods that may require physical contact or manipulation of the patient, 3D camera systems offer a non-invasive approach to weight estimation. This will enables a very rapid assessment of patients, particularly in fast-paced emergency situations where time is of the essence.
- Accessibility and portability: Modern 3D camera technology is becoming increasingly compact, portable, and cost-effective, making it suitable for deployment in diverse healthcare settings, including prehospital environments and field hospitals. The accessibility of these systems maybe able to empower frontline healthcare providers with advanced tools for accurate weight estimation, irrespective of location or resource constraints.
- Enhanced patient access: 3D camera weight may be able to estimation eliminates the need for patients to disrobe or undergo physical measurements to establish their weight. This non-invasive approach promotes a rapid and convenient weight estimation process.
- Integration with digital health platforms: 3D camera weight estimation can seamlessly integrate with digital health platforms and electronic medical records (EMRs), facilitating real-time data capture, analysis, and sharing across healthcare systems. By automating the documentation process, these systems maybe able to streamline clinical workflows and enhance communication among interdisciplinary care teams, leading to more informed and coordinated patient care.
- Personalized treatment algorithms: The precise weight measurements obtained through 3D camera technology enable the development of personalized treatment algorithms and medication dosing protocols tailored to individual patient characteristics. By accounting for variations in body composition and size, healthcare providers can optimize therapeutic interventions and minimize the risk of adverse drug reactions or treatment errors.
- Research and quality improvement: The utilization of 3D camera weight estimation in emergency medical care settings will be able to generate rich datasets for research and quality improvement initiatives. By capturing detailed anthropometric data from diverse patient populations, these systems may facilitate retrospective analysis, trend identification, and protocol refinement, ultimately enhancing the evidence base for emergency medical practices.

Given the existing work on weight estimation using 3D camera systems, it would be useful to review this work to identify current knowledge gaps, and to guide future research in the field

2 Literature review

An accurate measurement of body weight is crucial in many medical applications, including calculating medicine dosages, evaluating nutritional condition, and overseeing patient care in emergency situations. Historically, healthcare practitioners have utilized traditional methods of estimation, typically relying on visual indicators, clinical expertise, or basic instruments, to approximate a patient's weight. Nevertheless, these techniques, although commonly used, are susceptible to mistakes, particularly in time-critical situations such as emergency care, where precise weight assessment is crucial for establishing suitable treatment procedures.

Recent scientific progress in AI and machine learning has facilitated the development of more advanced weight estimation methods. Utilising extensive datasets and 3D imaging technology, artificial intelligence AI-based approaches have become increasingly popular because of their ability to enable more precise and automatic weight forecasts. Given the abundance of powerful computing resources and advanced deep learning frameworks, the incorporation of AI into medical operations has demonstrated encouraging outcomes, especially in domains where accuracy is of utmost importance.

This section aims to provide a comprehensive review of the existing literature on both traditional and AI-based weight estimation methods, highlighting key studies, trends, and the evolution of this field over time (Fig. 1).

2.1 Traditional methods

Establishing the weight of an individual is typically accomplished by direct measurement using a weighing scale. When an individual is unable to utilize a scale other indirect methods may be employed. For example, the weight of a hospital emergency department patient, which is extremely important to measure accurately, is often determined by asking the patient or a family member. If this information is not available, the weight is often estimated by hospital staff.

Traditional methods for obtaining a measure of body weight involve either direct measurement using weighing scales or indirect methods of weight estimation. If a measure of weight is needed and it cannot be measured, it must be estimated.

2.1.1 Weighing scales

Weighing scales are the predominant and precise means of directly determining human weight. These scales employ various techniques, such as spring scales or load cells, to ascertain the gravitational force exerted by an object. They are extensively utilized in medical settings, fitness clubs, and day to day life to measure weight. Nevertheless, weighing scales necessitate direct physical contact with an individual being measured, which may not always be feasible or convenient.

2.1.2 Weight estimation

Typical methods that can be employed for estimating body weight include:

- Self-estimates of weight by the person or patient themselves.
- "Guesstimates" of body weight by family members or healthcare personnel.

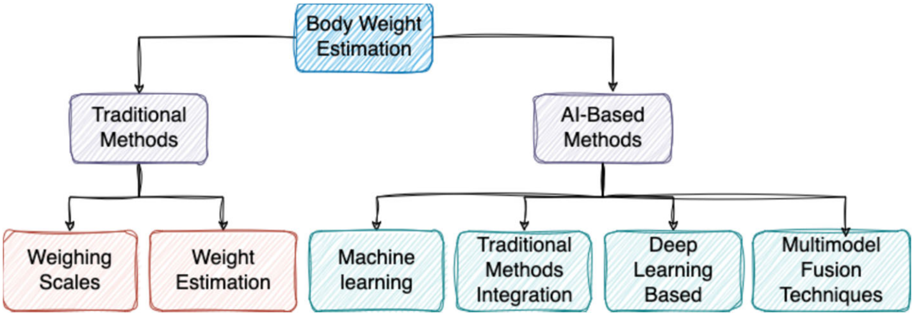


Fig. 1 Categorization of different methods for weight estimation

- Methods using formulas based on anthropometric measurements (body dimensions and proportions). These formulas may include combinations of height, segmental lengths (e.g., tibial length, humeral length), and body circumferences (e.g., mid-arm circumference, hip circumference, waist circumference).
- Tape-based weight estimation devices (e.g., the PAWPER XL-MAC tape which makes use of height and mid-arm circumference to provide a weight estimate).

These traditional methods have been extensively studied and in various populations. However, many of these methods are not sufficiently accurate, or may not be feasible to use under certain circumstances.

2.2 AI based weight estimates

2.2.1 Machine learning algorithms

Machine learning algorithms are increasingly being employed for weight estimation tasks due to their ability to learn complex patterns directly from data [10, 11]. Linear regression, support vector regression, or neural network-based regression models are trained to predict weight directly from extracted image features. Rativa et al. [12] explores the use of machine learning regression techniques to estimate height and weight from anthropometric measurements. By leveraging machine learning algorithms, the study aims to develop accurate prediction models based on a dataset of anthropometric data. The research focuses on improving the precision and reliability of height and weight estimation, potentially contributing to various applications in healthcare, fitness, and biometric identification. Similarly to adults, accurate weight in infants is important but the models developed for adults cannot be directly applied to infants due to the difference in body composition. Khan et al. [13] investigates infant birth weight estimation and low birth weight classification in the United Arab Emirates utilizing machine learning algorithms. By leveraging these algorithms, the research aimed to develop accurate prediction models grounded on relevant data. The findings of this study hold promise in advancing c enhance prenatal care by facilitating early interventions for infants at risk of low birth weight, contributing to improved maternal and child health outcomes in the UAE.

2.2.2 Traditional techniques integration

Recent studies have focused on integrating traditional weight estimation techniques [14–17], such as anthropometric measurements and weighing scales, with computer vision methods.

These integrative approaches aim to enhance accuracy and efficiency by leveraging the complementary strengths of both modalities. Fitriyah et al. [18] discusses and proposes a weight estimation system using a single 2-D snapshot of the front pose of a person Fig. 2, unlike a thermal or a Kinect camera as most other weight estimation researchers use. A 2-D snapshot allows for a quick process for weight estimation. Using the height, shoulder width, abdomen and arm width, and feet width of the body, this method uses image processing and multiple linear regression to estimate the weight of a person. Segmentation of the body from the background is used to get the Silhouette. However, with clothing and its effect on the outline of a body, the article recommends excluding the use of puffy clothing when taking the 2-D snapshot. By dividing the body into 8 equal segments, the location of the body parts can be extracted, allowing for a simple method to retrieve the necessary data. With this data, multiple linear regressions can be applied and output an estimated weight. This study reported on 10 adult males utilizing the coefficient of determination, R-squared, was used to see how well the regression fit the data. They found that a formula using all 4 features of the body obtained a higher R-squared value than only using a few of the features, showing that it is necessary to use all the variables, such as height, shoulder width, abdomen and arm width, and feet width of the body to determine a more accurate weight of the body. However, further work needs to be done to test the accuracy of this weight estimation method among various ages, genders, and ethnicities.

Also, Dantcheva et al. [19] proposes and tests the utilization of 2-D facial snapshots to estimate a person's weight, height, and BMI. This article critiques the absence of facial data

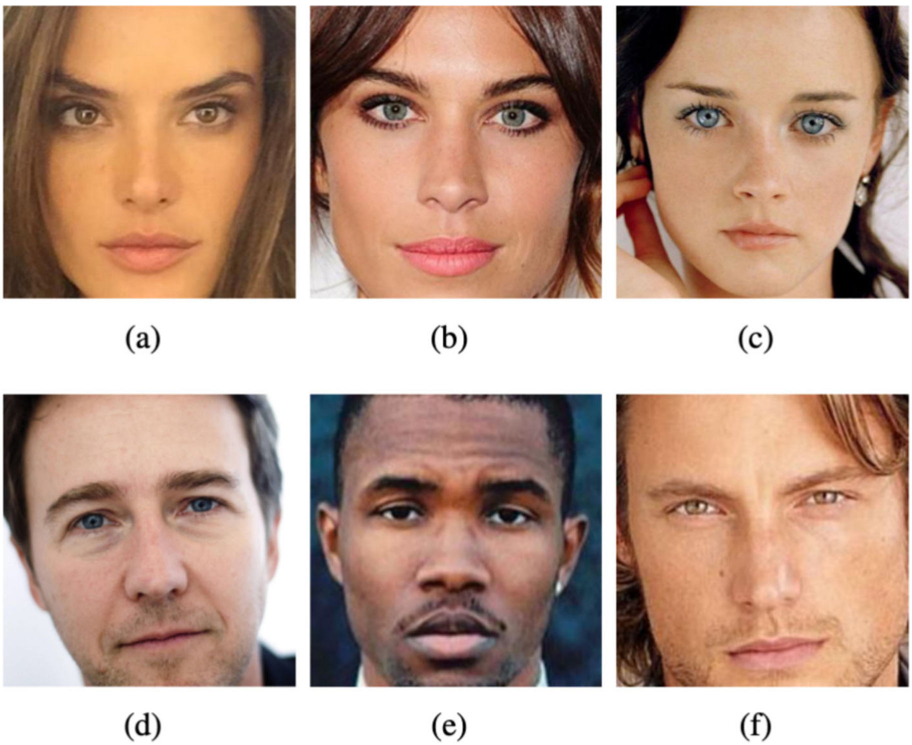
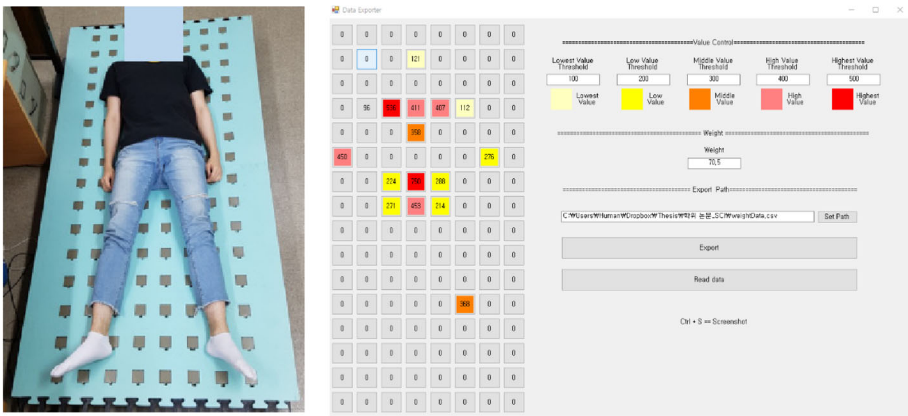


Fig. 2 Example of six subject from VIP attribute dataset [19]

in studies focusing on estimating weight, height, and BMI. This research uses a regression method based on ResNet50 architecture, consisting of 1026 subjects with 513 male and 513 female celebrities. Based on the data retrieved in this research, similar to body images and videos, it is concluded that facial images contain information about an individual's height, weight, and BMI. Through further research, this article reveals minimal disparity in weight estimation between male and female weight. Using the Viola-Jones face detection algorithm, detecting faces with 100% accuracy was possible. This data was then processed through ResNet-50 architecture, which is a deep neural network architecture used for deep learning and recognition tasks. Although the height and BMI estimations were relatively accurate, many challenges were faced with the weight estimations. The article highlights that these findings could be attributed to weight fluctuations over time, plastic surgery, makeup and beautification, or image alterations via Photoshop. It, suggests that a more robust data set could be used for the weight estimation in future research. In addition, the article emphasizes that more research can be done to test the accuracy of this height, weight, and BMI estimation method among various ages and ethnicities.

2.2.3 Deep learning architectures

Advancements in deep learning architectures, particularly convolutional neural networks (CNNs), have led to significant improvements in weight estimation accuracy [20]. Researchers have developed CNN-based models capable of extracting features from images and accurately predicting body weight, often outperforming traditional methods. Kim [21] proposes, and assesses three weight estimation techniques using 128 force-sensing resistor sensors arranged in a 16 × 8 grid structure on a smart mat Fig. 3. These methods used segmentation, average cumulative sum of pressure, and serialization. Each method employed regression, deep neural network, convolutional neural network, and random forest as the machine learning models for analysis. Utilizing MAE and RMSE as performance indicators, the serialization method with the deep neural network emerged as the most effective model. This approach yielded Mean Absolute Error(MAE) and Root Mean Squared Error(RMSE) values of 4.608 and 5.796, respectively.



(a) (b)

Fig. 3 Lying posture in the smart mat (a) and pressure distribution (b) [21]

The method had an overall error of ± 4.6 kg for the average weight of 72.9 kg. In addition, it is important to note that the MAE increased when the values of the lower $\frac{1}{3}$ of the forcing sensing resistor sensors were ignored, with the article discussing the importance of those sensors to determine the patients' lying posture which can change the estimated weight with this method. A limitation addressed in this paper concerns the concurrency of the dead zones arising from significant horizontal and vertical distances between the sensors. This issue resulted in over 75% of the sensors registering zero sensing values, resulting in a dropout effect in the data. Another downside of the dropout effect encountered in this study was a recognition error in which two samples with different body weights were classified as the same, which led to an increased estimated error. Despite these errors, the serialization method with the deep neural network still outperformed the other methods and still showed promising results. Another study [22] estimated body weight using five anthropometric parameters from 2D frontal body images. Waist width to thigh width ratio, waist width to hip width ratio, waist width to head width ratio, hip-width to head width ratio, and body area between waist and hip are used to estimate weight. A visual-body-to-BMI dataset of 5,900 photos of 2,950 participants was employed to examine the relationship between derived anthropometric parameters and BMI. This study evaluates a weight-estimating technique across three levels. The initial step involved comparing two photos of patient to determine if their weight changed Fig. 4. The second stage calculated how big of the difference between the subject in two photos were. The third stage was this technology's ability to predict a patient's BMI from one body image. This method overestimated BMIs between 20 and 30 years of age and underestimated those over 35 years. Huge poses, occlusion, loose clothing, and poor patient segmentation from the image background caused failures.

In contrast, another method examining body composition by Xie et al. [23] study examines and assesses the use of whole-body silhouettes. Silhouettes were generated using dual-energy x-ray absorptiometry whole-body scans Fig. 5. The ASM described the variation in silhouette form by computing major components for several shape modes. The study sample consisted

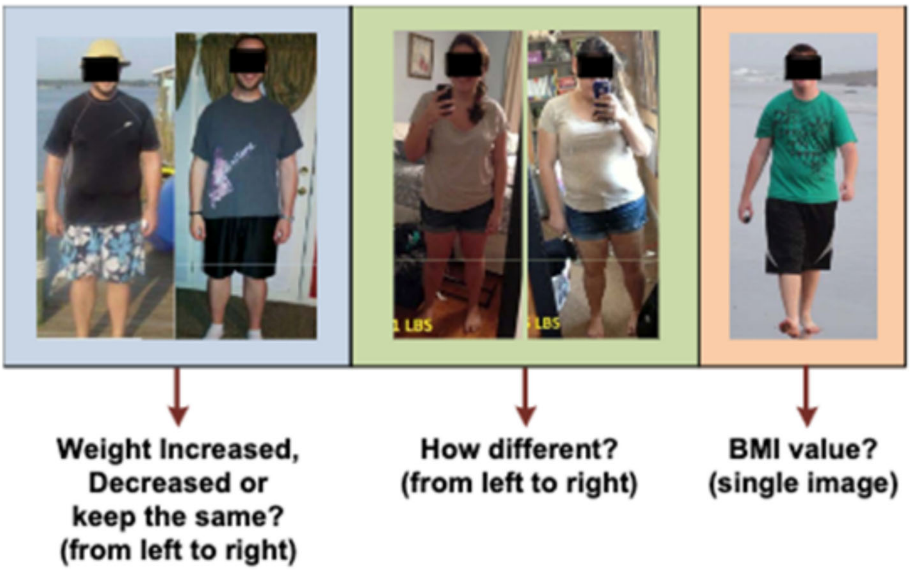


Fig. 4 Three categories of problem addressed in this study [22]

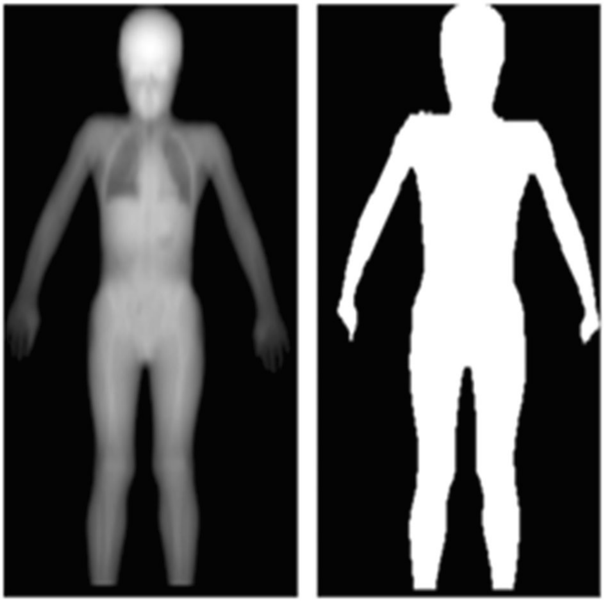


Fig. 5 Left- DXA scan, right - Silhouette of DXA scan [23]

of 200 healthy individuals aged 6-16. Stepwise linear regression was employed to develop prediction models using fat mass index, fat-free mass index, and percent fat modes. The models were compared to basic demographic-only models. Analysis showed that 26 patterns accounted for 95% of the diversity in form within the population studied. Both demographic-only and form-only models effectively predicted body composition, but the combination of shape and demographics provided more precise predictions for both genders. The most precise prediction models for fat mass index, fat-free mass index, and percent fat accurately forecasted actual measures with R2 values of 0.86, 0.95, and 0.75 for males and 0.90, 0.89, and 0.69 for females. The research shows that this method is appropriate for simple cameras such as cell phones.

Labati et al. [24] presented an innovative method designed for contactless, low-cost, unobtrusive, and unconstrained weight estimation based on frame sequences of a walking individual Fig. 6. This method offers a practical and feasible approach to weight estimation, capable of achieving view-independent results without the necessity of computing intricate models of body parts. Weight, identified as a soft biometric trait, stands out due to its unique combination of distinctiveness and permanence. This characteristic makes weight an especially valuable parameter in forensic applications, where reliable and consistent identification metrics are crucial. Park et al. [25] by using Weighing CAM, demonstrated exceptional accuracy and precision in predicting the weights of pediatric patients, surpassing the standard Broselow tape, a commonly used weight estimation system utilized in many emergency departments. The findings demonstrated a less prejudice and a greater proportion of estimated weights that were within 10% of the real weights. The findings indicate that the Weighing Cam can be a valuable instrument for estimating weight in pediatric resuscitation situations, offering advantages in both prehospital and hospital environments. Due to its improved precision and dependability, it can be a viable substitute for current techniques. This might lead to better patient care by enabling more precise medicine administration and customized treat-

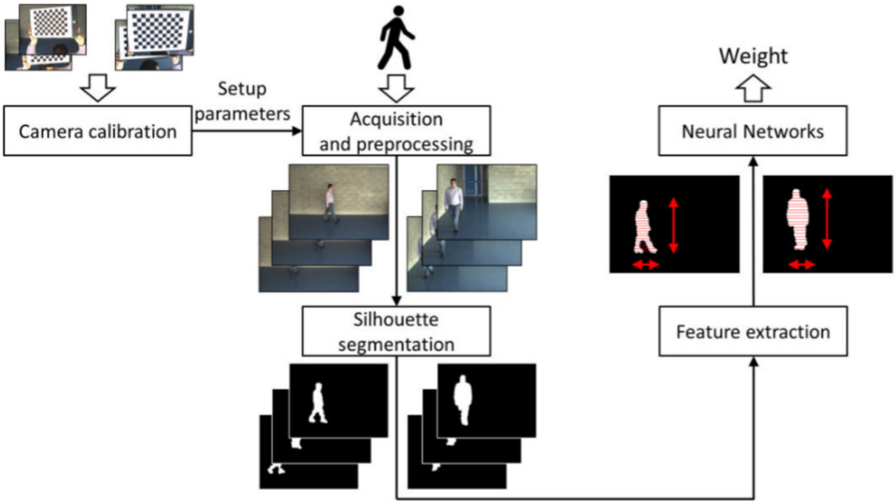


Fig. 6 Proposed study workflow by Labati et al. [24]

ment plans based on unique patient requirements. Geissler et al. [26] introduced an advanced technique for individualized computed tomography, which relies on a simulated digital twin as its basis. This method combines a 3D camera with artificial intelligence algorithms to automatically calculate both the height and weight. Through the utilization of sophisticated imaging technologies and analysis powered by artificial intelligence, the system offers a more efficient and precise method for producing individualized CT readings. This novel methodology not only guarantees to augment the precision of diagnostic processes but also presents prospective enhancements in treatment planning by customizing medical evaluations to specific patient features. Ichikawa et al. [27] recognizes various areas of research that require additional examination in the field of body weight estimation and computer modeling. First and foremost, it is widely acknowledged that there is a need to develop a new method that does not depend on diagnostic CT images in order to accurately estimate body weight. This discrepancy indicates a chance to investigate different approaches that could provide less intrusive and more readily available options for estimating weight. Furthermore, the study prompts inquiries about the applicability of the model's effectiveness in different clinical environments. Gaining insight into the model's performance across various locations and patient populations is essential for its wider implementation and acceptability. Furthermore, the possibility of applying the models to several scan ranges, such as from the neck to the pelvis, chest to pelvis, or abdomen to pelvis, offers additional avenue for investigation. By conducting additional research to address these deficiencies, the versatility and application of the proposed models could be greatly improved. This has the potential to result in more complete and trustworthy weight estimate approaches.

2.2.4 Multi-modal fusion techniques

Efforts have been made to incorporate multi-modal fusion techniques, combining information from multiple sources such as depth sensors, thermal imaging, and 3D body scans, to improve the robustness and generalization capabilities of weight estimation systems. These approaches aim to mitigate challenges related to variability in body types and environmental factors. Dane et al. [28] discusses the use of a 3-D camera to estimate the height and weight of patients. This study consists of 453 patients whose tomography images were analyzed. Through a 3-D camera mounted on the ceiling with infrared imaging and machine learning algorithms, the weight and height of these patients were accurately estimated. For training purposes, 363 Images were used with an additional 90 images were used as a test set. The estimations produced by the 3-D camera were compared to the actual height and weight measurements of the patients. The statistical analysis revealed a P value below 0.05 indicating a significant correlation between the estimated and true weight and height of the patients. A 3-D patient geometry was created by a Deformable Patient Avatar Representation with Deep Image Network which is then fitted onto the surface data from the 3-D camera. Furthermore, segmenting the 3-D model into separate regions such as the abdomen, thorax, head, arms, and legs was crucial to find the length and volume of these body segments, with the volume of the thorax and abdomen regions having greater significance for the estimations. The results showed that there was a 2.0% error in the height estimations and a 5.1% error in the weight estimations. Through further analysis, it was evident that the camera tended to slightly overestimate the weight of patients who were overweight, and slightly underestimate the weight of patients who were underweight. However, the overall accuracy remained high, showing the usefulness and practicality of using a 3-D camera with infrared imaging and machine learning algorithms for weight and height estimation. Cook et al. [29] discusses and tests the use of a Microsoft Kinect RGB camera infrared depth sensor device to accurately estimate patient volume. Through this method, a three-dimensional estimate of the patient size and density would be created for the use of modeling specific anatomy or promoting normalization of radiation dosage estimates. The patient stands on an electronic scale to obtain weight, while simultaneously having a depth math created Fig. 7.

Segmentation was used to isolate the subject from the background. Through the Microsoft Kinect device, a depth map of the subject is obtained, which is then used to estimate whole-body volume through a convex hull algorithm. From the estimated volume, a density estimate was calculated through dividing the patient's weight by their volume. The results of this study show the promising future of volume estimations through Microsoft Kinect 3-D imaging.

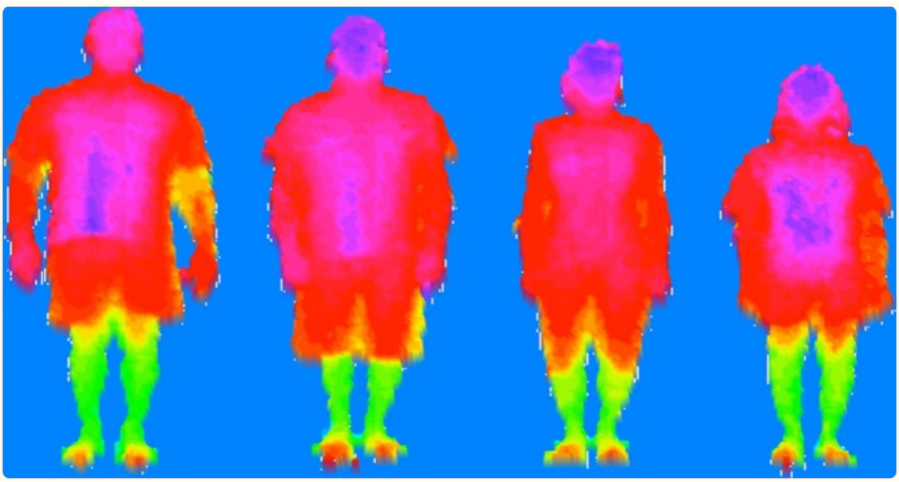


Fig. 7 Depth maps of 4 volunteers using Kinect Camera [29]

There was a correlation that was found between the volume estimates and the weight of the patients. However, arm positioning was a significant challenge faced in this study due to its effect on the volume estimates and density estimates. When the arms were extended more outward, the volume estimate tended to increase resulting in a lower density estimate. On the other hand, when the arms were not extended outward as much, the volume estimate tended to decrease, also leading to a higher density estimate. With this finding in consideration, it would be important to find methods for accurately calculating the volume and density of patients disregarding their arm position, an area for improvement in future research. Bigalke et al. [30] proposes a new approach for contactless weight estimation which considers the factors of patient position and visibility. In hospital environments, patients are covered by blankets or covers of some sort. This research aims to calculate the patient's weight whether or not the patient is covered, directly improving the usability and practicality of this research in a hospital environment. Through training a 3D U-net to virtually uncover the patient, the problem of visibility is tackled as predicting the patient's volumetric surface is now possible. The next step involves weight estimation in which the estimation is predicted from the 3D volume using a 3D CNN architecture for weight regression. Upon further analysis, it was found that this method of weight estimation improved by up to 16 percent and reduced the gap to weight estimates by up to 52 percent compared to baseline methods, even under the presence of a thick clothing. However, a domain shift between training and test data lead to a substantial drop in accuracy and performance in the cross-domain experiment, which is something that can be further studied and improved in future research. The article further discuss the usability of this research and how these findings and methods can be used beyond weight estimation, even venturing further into medical inconveniences in which the patient is covered by a blanket Fig. 8.

Mathematically, the process of weight estimation using the 3D CNN can be represented as:

$$W_{\text{est}} = f(V_{3d})$$

where W_{est} represents the weight of the patient, V_{3d} represents the 3D volumetric data, and f denotes the weight regression function learned by the 3D CNN.

The objective during training is to minimize the discrepancy between the predicted weight W_{est} and the ground truth weight of the patient. This is typically achieved by optimizing a loss function such as mean squared error (MSE) or mean absolute error (MAE):

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|W_{\text{est}}^{i} - W_{\text{gt}}^{i}\right|$$

where N is the number of training samples and W_{gt}^{i} is the ground truth weight of the ith patient in the training dataset.

Velardo et al. [31] proposed employing a Microsoft Kinect RGBD sensor to calculate patient weight by analyzing anthropometric factors generated from body silhouettes and 3D data. A statistical algorithm, trained on NHANES data, may predict a patient's weight by analyzing anthropometric measurements from more than 28000 patients Fig. 9. The Microsoft Kinect RGBD sensor can be used to obtain body silhouettes for anthropometric measurements. Outliers are removed by dividing body portions and measuring them separately to calculate the median value. The arm circumference measurements from a database of 15 individuals was less accurate because of insufficient Kinect resolution and quantization of depth values. The weight has a relative inaccuracy of 3.6% or an absolute mistake of 2.7 kg. The research proposes improving the strategy's precision by integrating many sensors,

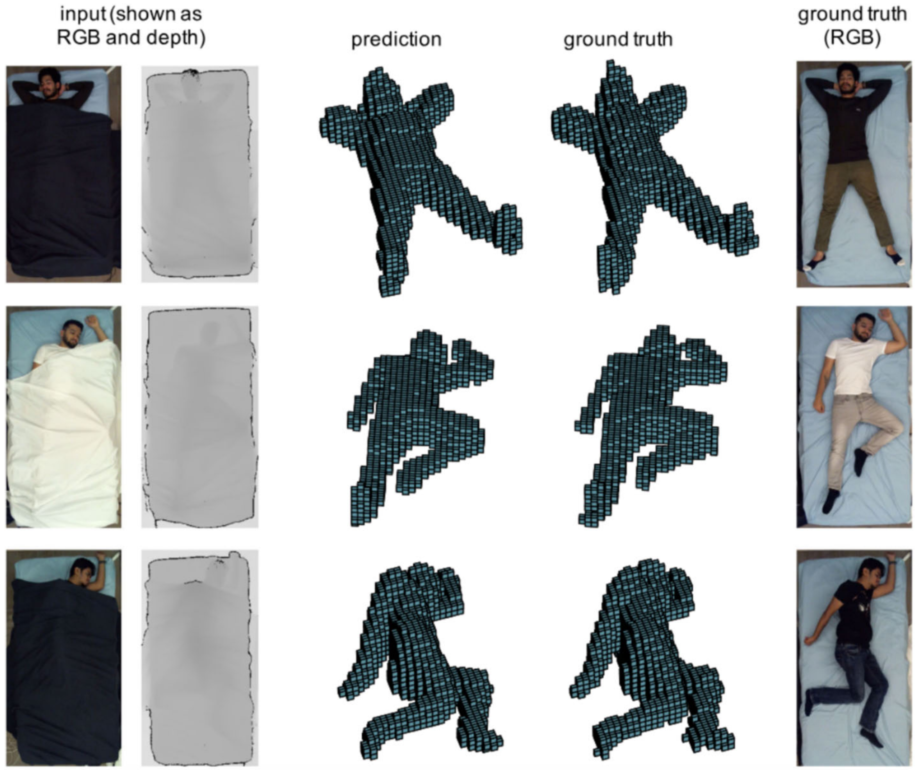


Fig. 8 Sample images from SLP dataset with ground truth and prediction made with 3d-CNN [30]

techniques, and modalities despite its encouraging findings. The same author also discusses and tests the use of extracting anthropometric data for weight estimation. Through multiple regression analysis, a model on a set of anthropometric features is retrieved. The model is trained through the NHANES database, with this method being tested on both ideal and realistic conditions. This method was tested in 3 steps on a dataset with 20 subjects consisting of 15 males and 5 female [32].

Singh [33] also presents the 3D patient geometric surface model DARWIN. This model uses the Deep Image Network to mimic the shape of a person sleeping under loose sheets. The patient's snapshot is taken using a Microsoft Kinect 2 range imaging device mounted on the ceiling and directed towards the hospital bed. Utilizing a convolutional neural network, the patient's posture was indentified. In addition, each patient has 15 body indicators that were used. The qualities effectively represent the body's skeletal structure. The final step of this process is matching 3D patient surface data with a trained patient-specific deformable mesh model. The approach was assessed on 1063 human participants from 3 hospitals, encompassing a wide range of ages, body types, sizes, clothing, and ethnic backgrounds. The initial experiment focused on evaluating the accuracy of posture and landmark detection. The pose classification network achieved a 99.63% accuracy on the testing data and 99.48% from PBT. They then analyzed the significant performance of patients with and without blankets. The comparison between patients with and without coverage shows a mean Euclidean distance error difference of less than 1cm for wrist landmarks and less than 0.4cm for all

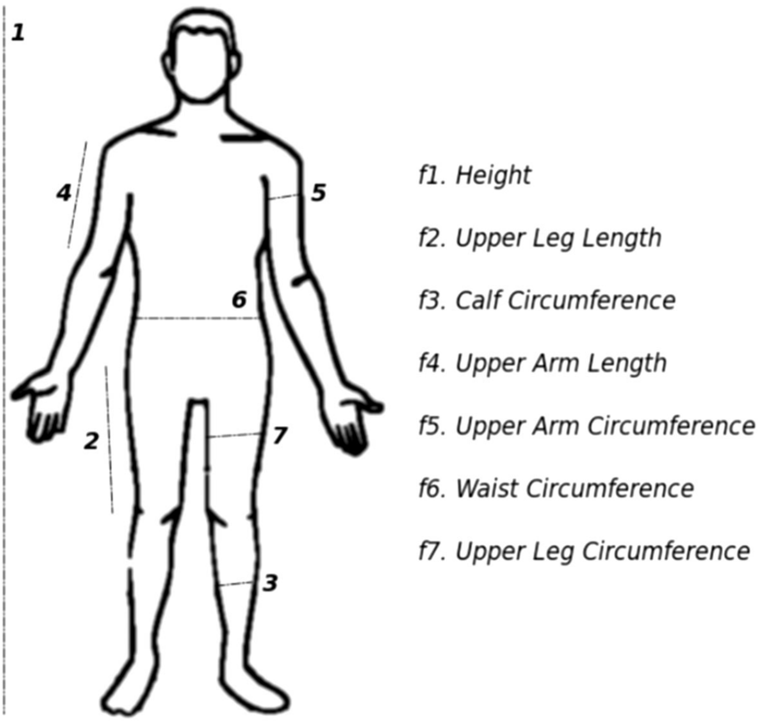


Fig. 9 Measurement that were taken into account [31]

other landmarks, demonstrating precise landmark learning even in covered individuals.To assess accuracy an experiment was conducted to compare the predicted patient mesh with the CT skin surface mesh using a dataset of 291 patients to evaluate its accuracy Fig. 10. The patient mesh prediction aligned with the CT skin surface accurately, even when clothing is present, due to extensive deep network training on varied patient datasets from many sites. The SCAPE model, excluding CT and gravity-simulated mesh training, decreased abdominal area error by 20%, which is the region with the most significant form distortion when transitioning from standing to lying down.

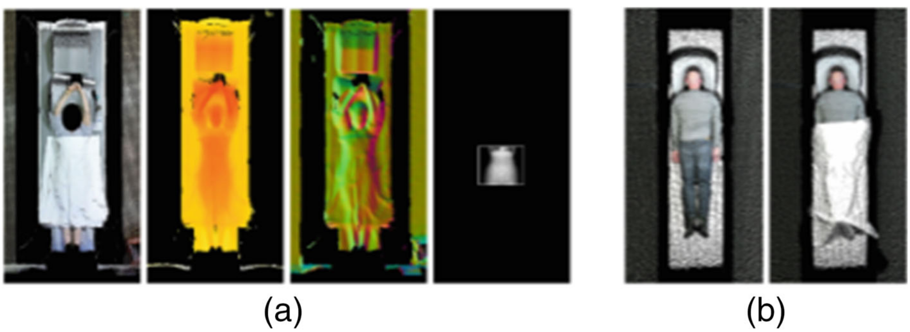


Fig. 10 (a) Different modalities data aligned (b) Images of subjects with and without cover

Pfitzner et al. [34–37] conducted multiple research investigations to investigate weight estimation methods utilizing different sensor technologies and data analysis approaches. They used a 3D structured light sensor in the initial study to calculate weight by analyzing patient segmentation and mesh generation. The procedure entailed isolating the patient from the background by utilizing axis-aligned bounding boxes and RANSAC for stretcher localization. The body volume was calculated by finding the difference in polyhedron-wise between the front and back surface meshes, while the surface area was determined using Heron's formula. Principal components analysis helped in predicting body length, which, when combined with volume calculations, resulted in weight predictions. Testing on 110 individuals demonstrated a 79.1% accuracy rate, with mistakes linked to small placement flaws and changes in lung volume. The second study included RGB-D and thermal cameras to collect depth and temperature data for weight estimation. Following calibrating and aligning images, the thermal camera assisted in segmenting patients. Multiple characteristics, such as volume and surface area, were obtained and fed into an artificial neural network. The approach attained a 90% accuracy rate in calculating weight which is above 72.4% accuracy of physician weight estimations. Future work includes incorporation of continuous weight calculation and evaluate novel sensor varieties Fig. 11. Anthropometric characteristics were obtained from RGB-D sensor data with Microsoft Kinect cameras and a thermal camera for segmentation in the third investigation. Various image processing techniques enhanced the segmentation outcomes. The artificial neural network was provided with features such as volume, surface area, and eigenvalues. The technique successfully reached an estimation range within $\pm 4.6\,\%$ for 94.8% of test individuals, highlighting the significance of feature selection and sensor choice. The author finally explored a multi-sensor strategy involving RGB-D cameras, Microsoft Kinect, Kinect One, and a thermal camera. The combination of data from these sensors helped in dividing patients into groups and extracting specific characteristics. The approach, evaluated on persons in both stationary and walking states, resulted in mean absolute errors of 4.3 kg and 5.20 kg, respectively. Gender inclusion was essential for precise weight estimation. Future research recommendations encompass utilizing larger datasets and developing methods to account for patient movement to enhance accuracy and ease. Naufal et al.'s [38] study emphasizes many notable progressions in the domain of body measurement and weight estimation. The researchers have successfully created a Matlab-based software that can automatically measure height and area using a Kinect camera, without the need for directly touching the people. The measurements exhibited a strong connection with conventional methods and maintained a low error rate, hence highlighting the correctness and

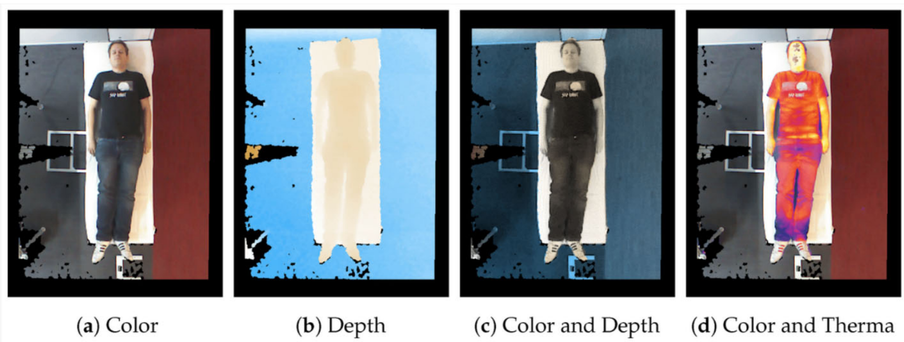


Fig. 11 Different data used by the authors in their studies [34, 36, 37]

dependability of the software. Furthermore, the investigation uncovered a robust association between the height and area measures of subjects and their corresponding weights. This link implies that these metrics can be reliable markers for predicting body weight. Furthermore, the implementation of an intuitive graphical interface not only improves the software's accessibility but also simplifies its usage. This interface enables effortless automatic calculation of body height and area. In summary, these discoveries signify a notable advancement in non-intrusive methods of measuring the human body. They hold great potential for use in healthcare and tailored medicine.

Tamersoy et al. [39] conducted a study that introduces an advanced technique for precisely determining the height and weight of patients in clinical imaging through the use of depth cameras. Their deep learning method, which was trained on a substantial dataset consisting of more than 1850 participants participating in 7500 clinical procedures, obtained impressive accuracy rates. Specifically, it achieved a height accuracy rate of 98.4% (PH5) and a weight accuracy rate of 95.6% (PW10). This technique greatly improves patient safety and imaging optimization by offering accurate readings even in uncontrolled clinical settings. The suggested technique represents a significant breakthrough in clinical imaging, with potential applications in diverse healthcare environments. Similarly, another study [40] investigates the possibility of utilizing deep learning and a 3D camera to automatically determine the height and weight of patients during MRI registration. This method improves the precision of gathering patient data, which is essential for optimizing MRI protocols. The results indicate that this approach has the potential to simplify the registration process, minimize errors caused by manual data entry, and enhance the overall effectiveness of clinical operations. Mameli et al. [41] also presented a framework named Top-View Weight Estimation (TVWE) that utilizes a top-view RGB-D camera to forecast body weight. This method utilizes Deep Neural Networks (DNNs) that have been trained on depth data. The top layers of the DNNs have been modified to forecast weights. The study evaluates the efficacy of five advanced deep neural networks (DNNs), namely VGG16, ResNet, Inception, DenseNet, and EfficientNet, in addition to a convolutional autoencoder. Assessed using the recently published "VRAI Weight Estimation Dataset," the framework shows encouraging outcomes, providing valuable information for use in health, business intelligence, and retail analytics Fig. 12.

Table 1 shows all the referenced published papers that used different techniques.

2.3 Applications in different domains

2.3.1 Healthcare

Computer vision techniques have been extensively applied in healthcare settings for various weight-related applications, including:

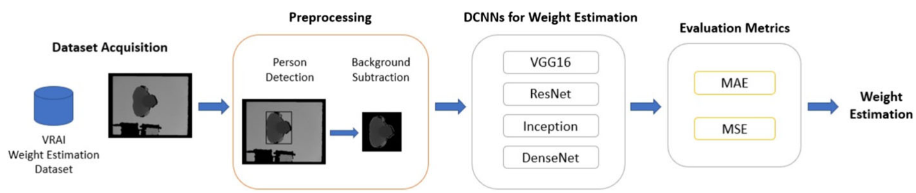


Fig. 12 Framework for TVWE [41]

Table 1 Overview of all included works

Ref #	Authors	Technique	Data type	Year
(15)	Corbo et al	–	Anthropometric	2005
(14)	Goutelle et al	–	Anthropometric	2009
(13)	Breuer et al	–	Anthropometric	2010
(30)	Velardo et al	Regression	X-Ray Images	2010
(40)	Darnis et al	–	Anthropometric	2012
(29)	Velardo et al	Segmentation + Regression	Numerical + Images	2012
(22)	Labati et al	Segmentation	2D Images	2012
(33)	Pfitzner et al	Segmentation	3D + Thermal	2015
(32)	Pfitzner et al	Segmentation	3D + Depth + Thermal	2016
(31)	Singh et al	Segmentation	Depth + CT images	2017
(34)	Pfitzner et al	Segmentation	3D Image + Depth	2017
(11)	Rativa et al	Regression	Anthropometric	2018
(35)	Pfitzner et al	Segmentation	3D images	2018
(16)	Fitriya et al	Segmentation	2D images	2018
(24)	Geissler et al	3D avatar construction	3D images	2020
(23)	Park et al	Weighing cam	Depth images	2020
(19)	Kim et al	DNN	Numerical	2020
(26)	Dane et al	Body segmentation	Image + Infrared	2021
(28)	Bigalke et al	Segmentation	3D images	2021
(39)	Mameli et al	DNN	Depth Images	2021
(25)	Ichikawa et al	CNN	CT images	2021
(12)	Khan et al	Regression	Anthropometric	2022
(36)	Naufal et al	Segmentation	3D images	2022
(37)	Tamersoy et al	DNN	3D + Depth	2023
(38)	Shahzadi et al	DNN	3D images	2024

Body weight monitoring Non-contact weight estimation methods using cameras enable continuous monitoring of patients' weight without the need for physical scales [42]. This is particularly useful for bedridden or immobile patients in hospitals or long-term care facilities. By integrating computer vision with smart monitoring systems, healthcare providers can track patients' weight fluctuations in real-time, allowing for early detection of health issues such as fluid retention or malnutrition.

Body composition analysis Beyond measuring body weight, computer vision can assist in analyzing body composition by estimating parameters such as body fat percentage, muscle mass, and bone density [43]. These measurements are valuable for assessing patients' overall health status, guiding treatment plans, and monitoring progress during rehabilitation or weight management programs.

Fall detection and prevention Sensors-based systems can also aid in fall detection and prevention among elderly [44] [Fig. 13] or vulnerable patients [45]. By analyzing gait patterns and body movements captured by cameras [46], these systems can detect abnormal behaviors indicative of an impending fall and trigger timely interventions, such as alerts to caregivers or automated assistance devices.

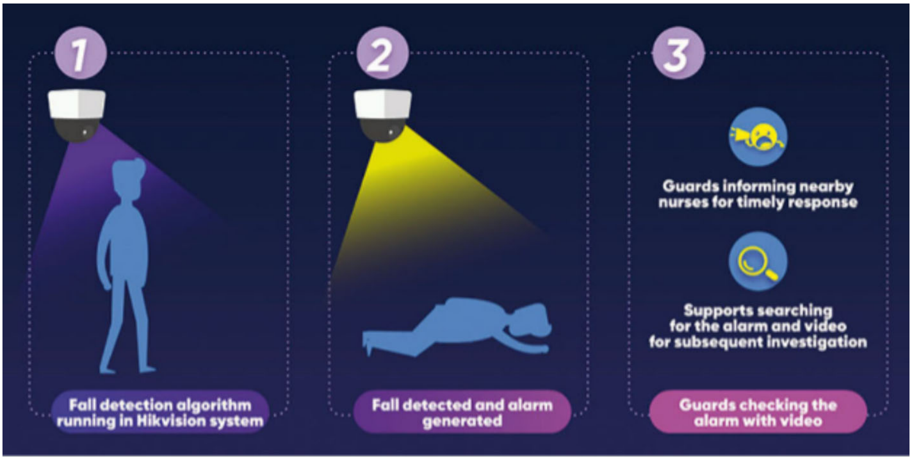


Fig. 13 Fall detection in assisted living and healthcare [47]

2.3.2 Fitness and sports

In the realm of fitness and sports, computer vision technologies offer innovative solutions for weight management, performance tracking, and injury prevention:

Body weight tracking Camera-based systems provide a convenient and non-invasive means of monitoring an individuals' weight changes over time. Fitness enthusiasts and athletes can use these systems to track their progress, set goals, and adjust training routines accordingly. By analyzing images or videos captured during workouts, these systems can estimate body weight and composition, providing valuable feedback for optimizing fitness regimens.

Biomechanical analysis Computer vision techniques enable detailed analysis of an athlete's movements and biomechanics, facilitating performance evaluation and injury prevention. By tracking joint angles, muscle activation patterns, and movement trajectories from video recordings, coaches and sports scientists can identify biomechanical imbalances or faulty techniques that may increase the risk of injury. This information can hwlp with personalized training programs aimed at improving performance and reducing injuries.

Sports analytics Computer vision is increasingly integrated into sports analytics platforms to extract valuable insights from game footage Fig. 14. By automatically detecting and tracking players, balls, and key events in sports videos, these systems provide coaches and analysts with data-driven insights for strategy development, player development, and opponent scouting. Weight estimation algorithms can also play a role in sports analytics by providing additional contextual information about a player's physical attributes and performance.

2.3.3 Security and surveillance

In security and surveillance applications, computer vision plays a crucial role in identifying and tracking individuals, detecting anomalies, and enhancing situational awareness:

Biometric identification Weight estimation algorithms can be integrated into biometric recognition systems for identifying individuals based on their physical characteristics. By

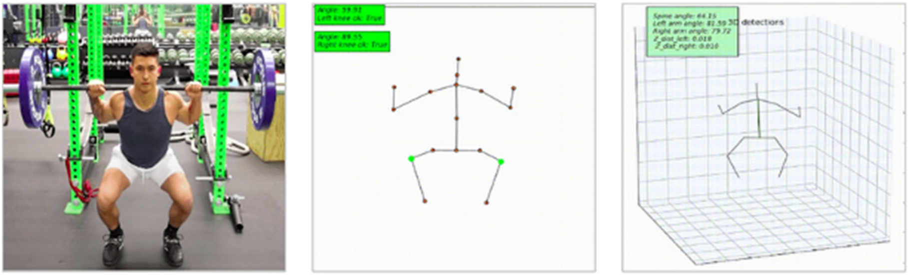


Fig. 14 Weight estimation in fitness [48]

analyzing images or videos captured by surveillance cameras, these systems can estimate a subject's weight and compare it with reference data to verify their identity. This capability is valuable in security checkpoints, access control systems, and forensic investigations.

Crowd monitoring Computer vision-based surveillance systems can analyze crowd dynamics and behavior patterns to detect suspicious activities or potential threats. Weight estimation algorithms contribute to this by providing insights into the size, density, and distribution of individuals within a crowd. By detecting anomalies in weight distributions or sudden changes in crowd density, these systems can alert security personnel to potential security risks or safety concerns.

Border security and immigration control Weight estimation techniques are also employed in border security and immigration control applications for screening travelers and detecting abnormalities. By analyzing images or videos captured at border checkpoints or immigration control points, computer vision systems can estimate travelers' weight and compare it with reference data to identify discrepancies or anomalies that may warrant further inspection.

2.4 Datasets and evaluation metrics

2.4.1 Commonly used evaluation metrics for weight estimation

In weight estimation using computer vision techniques, it is essential to employ appropriate evaluation metrics to assess the performance and accuracy of the developed algorithms. This section discusses several commonly used evaluation metrics for weight estimation research, along with their respective advantages and limitations.

Mean Absolute Error (MAE) MAE is one of the most straightforward metrics used to evaluate the accuracy of weight estimation algorithms. It measures the average absolute difference between the predicted weight values and the ground truth weights across all samples in the dataset [49]. MAE provides a simple and is an interpretable measure of prediction error, making it widely used in weight estimation studies.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right|$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, and N is the number of samples.

Root Mean Squared Error (RMSE) RMSE is another commonly used metric for evaluating the accuracy of weight estimation models. It calculates the square root of the average squared differences between the predicted and actual weight values. RMSE penalizes large errors more heavily than MAE, making it sensitive to outliers in the dataset [49]. However, RMSE may be less interpretable compared to MAE

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, and n is the number of samples.

Coefficient of determination (R-squared) R-squared, also known as the coefficient of determination, measures the proportion of variance in the dependent variable (i.e., actual weight values) that is explained by the independent variable (i.e., predicted weight values) in the regression model. A higher R-squared value indicates a better fit of the model to the data. However, R-squared may not capture the absolute accuracy of weight predictions and should be used in conjunction with other metrics.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2}$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of the observed values, and N is the number of samples.

Bland-Altman analysis Bland-Altman analysis is a graphical method for assessing the agreement between two measurement techniques or observers. In the context of weight estimation, Bland-Altman plots visualize the differences between predicted and actual weight values against their mean. This analysis provides insights into systematic biases, limits of agreement, and potential outliers in the weight estimation model.

2.4.2 Benchmark datasets for training and evaluation

HumanEva Dataset [50] The HumanEva dataset consists of synchronized video sequences and 3D motion capture data of human subjects performing various activities in controlled environments [50]. While primarily used for human pose estimation and action recognition, this dataset has also been utilized for weight estimation research by analyzing body shape and movement patterns (Fig. 15).

CK+ Dataset [51] The CK+ (Cohn-Kanade) dataset contains facial expression images of subjects displaying various emotions under controlled conditions [51]. While not specifically designed for weight estimation, researchers have leveraged facial features and expressions as proxies for weight-related attributes in certain contexts.

CAESAR Dataset [52] The CAESAR (Civilian American and European Surface Anthropometry Resource) dataset comprises 3D body scans and anthropometric measurements of a diverse population of individuals. This dataset provides detailed information on body shape, size, and proportions, making it valuable for developing weight estimation algorithms based on visual cues.

Medical Segmentation Decathlon [53] The Medical Segmentation Decathlon (MSD) [53] dataset is a prominent resource in medical imaging, offering a diverse collection of annotated medical images across ten segmentation tasks. With annotations provided by expert clinicians,

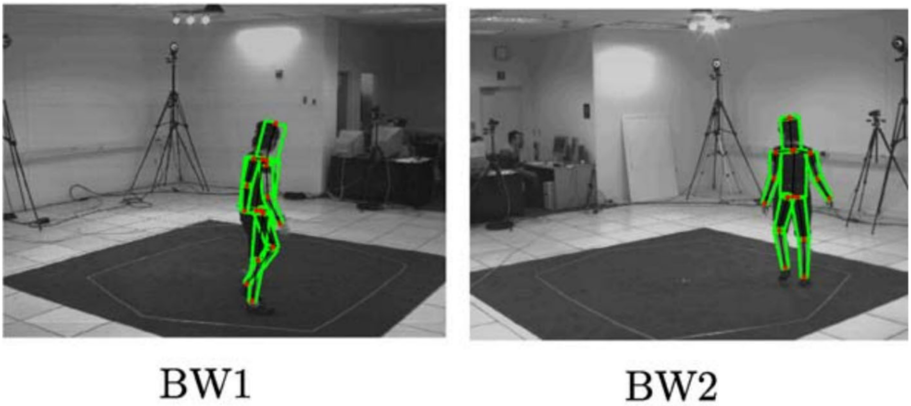


Fig. 15 Benchmarking datasets for weight estimation

the dataset serves as a standardized benchmark for evaluating segmentation algorithms across various anatomical structures and imaging modalities. Researchers can utilize the MSD dataset to train and validate segmentation models, enabling advancements in medical image analysis for improved clinical decision-making and patient care.

PETA Dataset [54] The PETA (Person Re-identification Dataset) dataset contains images of individuals captured by surveillance cameras in outdoor environments [54]. Although not specifically tailored for weight estimation, this dataset offers a diverse range of poses, clothing styles, and lighting conditions, presenting challenges similar to real-world scenarios.

Kinect Body Tracking Dataset [55] The Kinect Body Tracking dataset provides depth images and skeletal joint data captured by Microsoft Kinect sensors during human activities [55]. This dataset facilitates the development of weight estimation algorithms by analyzing body shape and movement information extracted from depth images.

MORPH-II [56] The MORPH-II dataset is a well- regarded benchmark dataset that is widely utilized in the domains of face recognition and age progression research. The dataset comprises a vast assortment of facial photos obtained from various ethnic backgrounds and covering a broad age range. The dataset comprises high-resolution photographs of humans over a wide range of age groups, spanning from infancy to old age. In addition, the MORPH-II dataset includes annotations for age, gender, and ethnicity, allowing researchers to perform thorough studies and create strong algorithms for tasks such as age prediction, facial recognition, and demographic classification. Before being used in research investigations, the MORPH-II dataset usually goes through preprocessing and cleaning methods to eliminate duplicates, guarantee uniformity in annotations, and improve data quality.

W8-400 [57] The dataset "Seeing Human Weight from a Single RGB-D Image" is a notable breakthrough in the field of computer vision for estimating weight. This collection consists of RGB-D photos that capture human individuals from different perspectives and postures. Every photograph contains abundant visual and depth data, enabling precise calculation of human weight without the necessity of real scales. Researchers can create strong models that can estimate weight using only visual cues by utilizing machine learning algorithms and depth information extracted from RGB-D photos. The dataset enables the training and evaluation of models, promoting progress in healthcare, fitness tracking, and biometric identification applications. Moreover, this dataset aids in the overall objective of creating non-intrusive and easily accessible techniques for weight estimates, thereby improving the effectiveness and ease of weight monitoring in diverse situations.

Face-to-BMI [58] This paper [58] presents a pioneering method leveraging deep learning techniques to estimate Body Mass Index (BMI) from facial images. The dataset utilized in this study comprises a diverse collection of facial images sourced from individuals with varying BMI values collected from different datasets [19, 59, 60]. These images capture facial features and expressions, providing rich visual data for BMI estimation. Each image is associated with corresponding BMI measurements, enabling the training and validation of deep learning models for BMI prediction based solely on facial characteristics. By harnessing the power of convolutional neural networks (CNNs) and facial feature extraction, this dataset facilitates the development of accurate and scalable solutions for BMI estimation, with potential applications in healthcare, fitness assessment, and personalized wellness management. Additionally, the dataset's diversity in terms of age, gender, and ethnicity ensures robustness and generalizability of BMI estimation models across different demographic groups.

SLP Dataset [61] The Simultaneously multimodal Lying Pose Dataset represents a pioneering resource in the domain of human pose monitoring, specifically focusing on in-bed scenarios. This dataset captures a diverse range of lying poses using multiple modalities, including visual and depth sensors. Each data sample is meticulously annotated with key points corresponding to different body parts, providing comprehensive information about body posture and position. With a focus on in-bed monitoring, this dataset offers valuable insights into human movement and posture during rest or sleep, which can inform various healthcare applications such as patient monitoring, sleep disorder diagnosis, and rehabilitation. By enabling the development and evaluation of pose estimation algorithms tailored to in-bed scenarios, the dataset contributes to advancements in assistive technologies and personalized healthcare solutions, ultimately enhancing the quality of patient care and well-being.

PMAT Dataset [62] This dataset utilized force-sensitive pressure mapping mattresses to record data, featuring 2048 sensors arranged in a 32 by 64 grid, with each sensor spaced 25.4 mm apart. Recording occurred at a frequency of 1 Hz, capturing pressure readings ranging from 0 to 100 mmHg. Thirteen healthy individuals were observed in eight standard positions and nine additional sub-positions, resulting in seventeen distinct pose categories. Participant characteristics included heights ranging from 169 to 186 cm, weights ranging from 63 to 100 kg, and ages ranging from 19 to 34 years. To label important body part points in 18256 data samples, we developed and employed a MATLAB method. Annotation was conducted by two researchers and subsequently verified to ensure consistency. To ensure rigorous assessment, we employed a leave-some-subjects-out validation technique. This involved training the network using data from 9 participants and testing its performance on the remaining 4 subjects.

HRL-ROS [63] Data collection for kinematic-based 3D pose recognition was conducted by Clever et al. [63] using a custom-configured bed embedded with pressure sensors and motion capture cameras. The bed featured an array of 27×64 sensors distributed 28.6 mm apart. Seventeen subjects participated, assuming various lying or sitting postures and performing specific limb movements while their positions were tracked using motion capture cameras. Subjects' characteristics included heights ranging from 160 to 185 cm, weights ranging from 45.8 to 94.3 kg, and ages ranging from 19 to 32 years.

These benchmark datasets in Table 2 serve as valuable resources for researchers and practitioners working on weight estimation using computer vision techniques. Figure 16 shows sample images for multiple datasets. By leveraging these datasets, researchers can advance the state-of-the-art in weight estimation algorithms, address challenges related to variability in body shape and appearance, and ultimately contribute to improved applications in healthcare, fitness, and security.

Table 2 Overview of existing datasets

Dataset	Type	Purpose	Modalities	Size	Annotations	Applications
HumanEva	Human motion	Human pose estimation and action recognition	RGB video and 3D motion capture	Moderate	3D Joints position and action labels	Human-computer interaction, animation, surveillance
CK+ Dataset	Facial expression	Facial expression analysis	Facial images	920	Expression labels	Emotion recognition, affective computing, psychology
CAESAR	Anthropometric	Anthropometric measurements	3D body scans	Large	Body measurements, body shapes	Apparel design, ergonomics, product development
Medical segmentation Decathlon	Medical imaging	Medical image segmentation	MRI, CT, X-Ray	Large	Segmentations	Medical diagnosis, treatment planning, research
PETA	Person reidentification	Person reidentification	Surveillance images and CCTV	Large	Person identities, attributes	Security, surveillance, law enforcement
Kinect body tracking	Human motion	Human motion and tracking gesture recognition	Depth images and skeletal joint data	315+	Skeletal joint position	Gaming, human-computer interaction, rehabilitation

Table 2 continued

Dataset	Type	Purpose	Modalities	Size	Annotations	Applications
MORPH-II	Face recognition	Face recognition and age progression	Facial images	55k+	Age, gender, ethnicity	Biometric identification, age progression research
W8-400	Weight estimation	Weight estimation from images	Depth images and RGB images	400	Weight measurements	Healthcare, fitness monitoring, biometric identification
Face-to-BMI	Face recognition	BMI estimation from facial images	Facial images	4.2k+	Body mass index	Healthcare, fitness assessment, personalized wellness
SLP	Pose estimation	Human pose estimation	RGB-D and 3D skeletal data	14.5k+	Pose annotations	Rehabilitation, biomechanics, sports science
PMAT	Pressure mapping	Pressure mapping for body posture analysis	Pressure sensor data	19k	Body pressure distribution	Ergonomics, posture analysis, healthcare
HRL-ROS	Robot sensing	Human robot interaction and sensor data	Robot sensor data	28k	Human-robot interaction data	Human-robot collaboration, assistive robotics

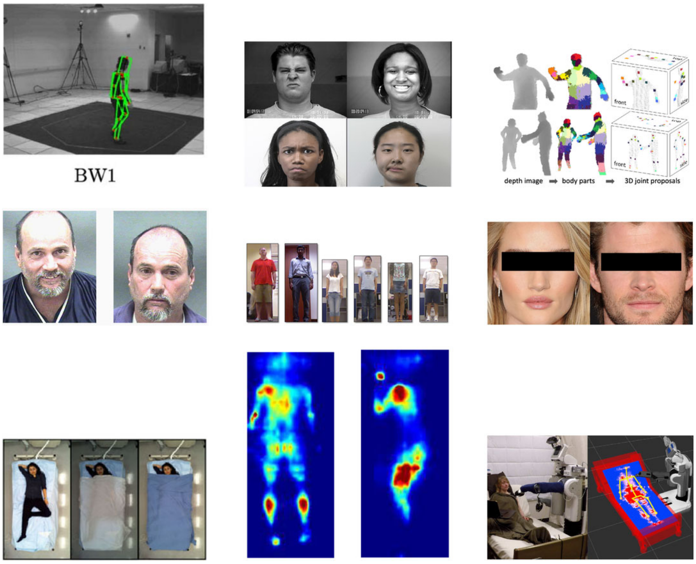


Fig. 16 Sample images for multiple datasets available for body weight estimation

2.5 Challenges and limitations

2.5.1 Variability in body types

One of the significant challenges in weight estimation using camera-based techniques is the variability in body types among individuals. Human bodies come in diverse shapes, sizes, and proportions, leading to significant differences in appearance that can impact the accuracy of weight estimation algorithms. The effectiveness of these algorithms may vary across different demographic groups, such as age, gender, and ethnicity, due to differences in body composition and morphology . Addressing this challenge requires developing robust algorithms that can adapt to the wide range of body types encountered in real-world scenarios.

2.5.2 Environmental factors

Environmental factors, such as lighting conditions, background clutter, and camera angles, can introduce variability and noise in the captured images, affecting the performance of weight estimation algorithms. Poor lighting conditions or uneven illumination may obscure important visual cues, while cluttered backgrounds can interfere with object segmentation and feature extraction. Moreover, variations in camera viewpoints and distances can distort body proportions and shapes, leading to inaccuracies in weight estimation [45]. Overcoming these environmental challenges requires robust preprocessing techniques and algorithmic adaptations to enhance the robustness and reliability of weight estimation systems in diverse environments.

2.5.3 Privacy concerns

The deployment of camera-based weight estimation systems raises privacy concerns related to the collection and processing of personal biometric data. Cameras capture detailed visual information about an individual's body, raising potential privacy risks and ethical considerations regarding data security and consent. Unauthorized access to sensitive biometric data or its misuse for surveillance purposes could compromise an individual's privacy rights and lead to legal and ethical implications [64]. To address these concerns, stringent privacy safeguards, such as data anonymization, encryption, and user consent mechanisms, must be implemented to protect individuals' privacy while ensuring the responsible use of biometric technologies.

2.5.4 Real-time implementation challenges

Real-time implementation of camera-based weight estimation algorithms poses technical challenges related to computational efficiency, latency, and hardware requirements. Achieving real-time performance requires optimizing algorithms for efficient computation and minimizing processing time while maintaining accuracy. Additionally, deploying these algorithms on resource-constrained platforms, such as mobile devices or embedded systems, may require hardware acceleration or specialized optimization techniques [43]. Balancing the trade-offs between accuracy and computational efficiency is crucial for practical real-time deployment of weight estimation systems in various applications.

3 Future directions

Potential areas for future research involve augmenting dataset variety by integrating data from a wider spectrum of demographics, strengthening the precision and applicability of weight estimate techniques. By combining data from several sensors and modalities, such as RGB-D cameras and thermal cameras, we may gain a more comprehensive picture of patient characteristics. This, in turn, will improve the accuracy of segmentation and the extraction of features. Advancing the optimization of algorithms and hardware to accurately estimate weight in real-time is a significant field of development. This progress enables prompt adjustments in patient care. Finally, by including data anonymization, secure transmission, and gaining informed consent, ethical and privacy concerns can be addressed, ensuring the confidentiality of patient information and compliance with privacy legislation. This will help build trust in the technology.

4 Conclusion

In this review we explored novel sensor-based techniques for measuring weight, showing encouraging outcomes in accurately predicting the weight of patients. The surveys and studies have yielded useful insights into the viability and efficacy of various weight estimation methods, providing a full overview of the current cutting-edge techniques. The framework for further breakthroughs has been established through the identification of future directions, including boosting dataset variety, integrating multimodal data, advancing real-time implementations, and resolving ethical concerns. This research not only enhances weight estimation technology but also showcases the potential of sensor technology in wider healthcare applications. Subsequent investigations hold the potential to enhance and broaden existing approaches, resulting in weight estimation methods that are more precise, dependable, and applicable for therapeutic purposes.

Data Availability No associated data.

Declarations

Conflict of Interest Muhammad Tanveer Jan would like to disclose that Borko Furht is an author of this manuscript and also serves as the Editor-in-Chief of Multimedia Tools and Applications. To ensure transparency, Borko Furht has recused himself from any editorial decisions regarding the handling and review of this manuscript. All editorial decisions have been made independently by other members of the editorial board.

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